A new method to estimate the state of lithium ion battery capacity using Chaos optimization-Least Squares Support Vector Machine

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ABSTRACT

In this paper, new algorithm is proposed to estimate the state of lithium ion battery capacity using Chaos optimization-least squares support vector machine. Here ,at first we had set parameters of the least squares support vector machine using Chaos optimization algorithms. Next we had made the regression model of least squares support vector machine using Gaussian kernel function. Also it had estimated the state of lithium ion battery capacity using Chaos optimization-least squares support vector machine.And the exactness on the estimation model of Chaos optimization-least squares support vector machine had verified through the simulation analysis.

Keywords: LS-SVM, Chaos, SOC, estimation, particle filter

1.Introduction

Lithium ion battery is widely used to supply power of every mobile equipment including mobile and smart computer, mobile phone, handheld camera, digital camera, motorcycle, airplane, missile and submarine because it has several advantages of light weight, high working voltage, excellent efficient of memory, no environment pollution and so on[1].

Ensuring the stability and reliability of Ferric Phosphate Lithium Ion battery to estimate the rest capacity and capacity state correctly in real-time is very important. There are several methods such as Coulomb scaling method(A**Error! Reference source not found.**h integration), open circuit method, Back Propagation(BP), neural net algorithm, Kalman filter algorithm and Particle filter algorithm[2-7].

Coulomb scaling method is the most simple one, so widely used in a lot of aspects including electric car.

In this method, SOC formula is used to calculate the charged and discharged capacity by integrating the current.

But the current sensor itself has error of measurement, so if this method is used in SOC prediction, the current measurement error is accumulated thus increasing the errors.

In case of open circuit voltage method, the relative equation between open circuit voltage and SOC is used, and this time open circuit voltage has to be measured enough.

The method based on BP neural network algorithm is artificial intelligence method of simulating the model using input and output samples[2].

But the method based on neural network requires a lot of sample data for study and prediction error is strongly affected by the quality of study data and study method.

Kalman Filter(KF) is reasonable data processing method proposed by Kalman in 1960[3, 4].

KF algorithm does not depend on the initial value of SOC but it can predict the accurate value of SOC.

But the correctness of this method depends highly on the building of equal circuit model of battery and it is limited as some physical characteristics of battery model are nonlinear.

In order to overcome this fault of KF algorithm, Extended Kalman Filter algrithm(EKF) and Unscented Kalman Filter algorithm(UKF) are proposed.

And Particle Filter is the method based on random sample used for the treatment of non-linear Gaussian problems[5].

The basic principle of this method is to use random samples (particles) with weight in state space. for approximation of priori probability density function of system states[6-11].

PF algorithm is relatively simple but correctness decreases when sampling.

Thus, there have been a lot of attempts to use support vector machine, new study machine based on statistics theory for real time capacity prediction of Lithium ion battery.

In this paper, real-time capacity estimating method of Iron Phosphate Lithium Ion battery is proposed using Chaos optimization-least square support vector machine and least square support vector machine model is compared and analyzed with and particle filter model.

2. The conception of Chaos and least square support vector machine

2.1. Chaos

Chaos theory is an important means to research the nonlinear phenomena and a branch of science to research and treat “internal randomness” in the dynamic system of nonlinear determinism.

One of the major problems in bionomics is change process of any species or several species of individual number of group over long time.

When individual number is N(t), the growth model of individual number(number of people, animals, etc.) can be modeled as

$$\frac{dN}{dt} = \gamma \frac{(k-N)}{k} N \tag{1}$$

Here k is a constant and if N is smaller than k, N increases and if N is greater than k N decreases and if N equals k, increasing speed is zero.

And γ, proportional constant, is related to the individual kind and environment.

Let's change the growth model into difference equation.

$$\frac{N(t+\Delta t) - N(t)}{\Delta t} = \gamma (1 - \frac{N(t)}{k}) N(t) \tag{2}$$

Let's do discretization at $t = t_1, t_2, \cdots, t_n, t_{n+1}, \cdots$

Let $N(t_n) = N_n$, and then

$$\frac{N_{n+1} - N_n}{\Delta t} = \gamma (1 - \frac{N_n}{k}) N_n \tag{3}$$

$$\frac{N_{n+1}}{\Delta t} = \frac{1}{\Delta t}(1 + \gamma \cdot \Delta t) N_n - \frac{\gamma}{k} N_n^2$$

and then

$$\frac{\gamma \cdot \Delta t N_n}{k(1+\gamma \Delta t)} = x_n, \quad \frac{\gamma \cdot \Delta t N_{n+1}}{k(1+\gamma \Delta t)} = x_{n+1} \tag{4}$$

$$1 + \gamma \cdot \Delta t = \alpha \tag{5}$$

From Eq. (4), (5) we get next equation.

$$x_{n+1} = \alpha (1 - x_n) x_n \tag{6}$$

Let $\lim_{n \to \infty} x_n = \bar{x}$ and initial value be x_0 (7)

In the case that ($0 \le \alpha \le 3$), the limitation of $\{x_n\}$ has one limitation irrespective of the initial value, there is no limitation of $\{x_n\}$ and approaches two values alternately if α is over 3 and approaches several values alternately with the increase of α and approaches unknown values randomly if α is over 4.

We didn't predict such irregularity in the process of solving the equation.

This phenomenon is Chaos and the progressions at this time are Chaos ones.

Chaos theory is widely applied in several aspects including global optimization calculation, nonlinear estimation, nonlinear vibration analysis, turbulence analysis and artificial intelligence, space engineering, atmospheric check, aerodynamics, biology, medical diagnosis.

2.2 Least square support vector machine.

SVM-Support Vector Machines is widely used in the intelligent treatment such as pattern recognition, filtering, control, diagnosis and pattern classification in 2000s[12, 13].

Least Squares–Support Vector Machines is more developed studying machine of support vector machine newly proposed by Sukens and Vandewalle, where unequal equation restrictive condition was changed by equal equation one and relaxation variable was introduced in the object function.

Least square support vector machine defines the following optimization problem using given study data($\{X_i, y_i\}_{i=1}^{l}$, where l is number of study data).

$$\min \ J(w, \xi) = \frac{1}{2} w^T w + c \cdot \frac{1}{2} \sum_{i=1}^{l} \xi_i^2 \ , \quad c > 0 \tag{8}$$

Restrictive condition

$$y_i = w^T \cdot \varphi(x_i) + b + \xi_i \ , \qquad i = 1, 2, \cdots, l$$

Here ξ_i is relaxation variable(slack variable), c is normalization variable, $\varphi(\cdot)$ is nonlinear function changing the input space into high order characteristic space, w is a vector of characteristic space and b is aberration term.

3. Estimation algorithm of state of Lithium Ion battery capacity using Chaos optimization-least square support vector machine.

Modeling stages using Chaos optimization least square support vector machine are composed of 3 stages, that is, parameter setting stage by Chaos optimization algorithm, modeling stage of least square support vector machine and estimation stage of data.

3.1. Parameter setting stage using Chaos optimization algorithm

(a) $k=1$, vector x^1 (It refers to σ and γ of LSSVM), T(allowed maximum search time), $f(x)$ (object function), $[a_i, b_i]$ (area of x_i^1), x^* (optimum value of $f(x)$) are given.

When searching begins, initial value of x^* is x^1 and that of f^* is $f(x^1)$.

(b) The space of solution is transformed into Chaos space $[0, 1]$ by the next equation.

$$t_i^1 = \frac{(x_i^1 - a_i)}{(b_i - a_i)} \tag{9}$$

(c) Chaos repeat row for t_i is generated using logistic transformation and then replaced with selected better value.

$$t^{k+1} = \eta t^k (1 - t^k) \tag{10}$$

where t is Chaos variable, and $0 \le t^l \le 1$, k is repetitive time and η is control parameter. When $\eta = 4$, it can be verified easily that system is in the whole Chaos state and Chaos space is $[0, 1]$.

(d) Chaos space is transformed into solution space.

$$x_i^{k+1} = a_i + (b_i - a_i) t_i^{k+1} \tag{11}$$

(e)Chaos disturbance operation is done and adaptive value($f(x^{k+1})$) is calculated.

$$l_k^{'} = (1-\alpha)l^* + \alpha \cdot l_k \quad (12)$$

where l^* is vector obtained by transforming the optimum value(x_1^* , x_2^*, $\cdots$, x_n^*) into $[0,1]$ and this is called optimum Chaos value.

l_k is Chaos variable after repetition of k times and $l_k^{'}$ is Chaos variable receiving Chaos disturbance and $0<\alpha<1$, and can be changed appropriately.

Large variation domain of variables is hopeful on initial stage of search, and thus, the value of α is greater on this stage.

The variable gradually approaches optimum value as search goes on, so value of α decreases gradually.

The value of α is determined using the following equation.

$$\alpha = 1 - \left|\frac{k-1}{k}\right|^p \quad (13)$$

where p is whole number and is determined by cost function and k is repetitive time.

(f) The value of $f(x^k)$ is compared with $f(x^{k+1})$.

If $f(x^{k+1})$ > $f(x^k)$, let $k=k+1$ and then go to (b) otherwise, let $x^* = x^{k+1}$, $f^* = f(x^{k+1})$ then go to (g).

(g) If $k<T$, let $k=k+1$ then go to (b) otherwise x^* is output.

3.2. The modeling stage of least square support vector machine.

Gaussian kernel function is selected kernel function, and it is expressed as

$$K(x,\ x_i) = \exp\{-\frac{\|x-x_i\|^2}{2\sigma^2}\} \quad (14)$$

LSSVM regression model is written as

$$y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b \quad (15)$$

3.3. Estimation stage of data.

Output data are estimated by inputting the test samples into the model with selected parameters.

Generalization performance is improved by adding new study samples into model and studying them.

Block diagram of real time capacity state estimation model of Lithium Ion battery based on Chaos optimization-least square support vector machine is shown in Fig 1.

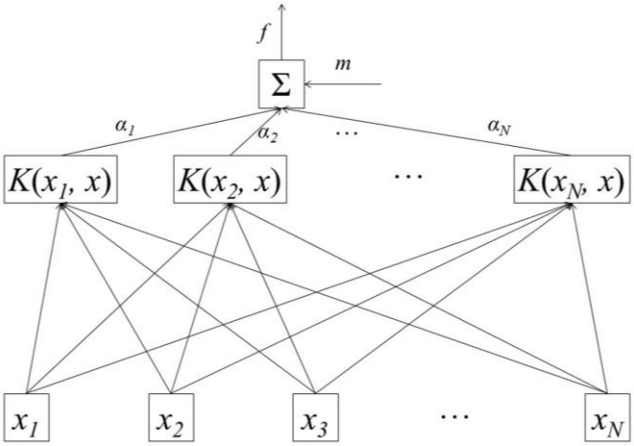


Fig. 1. Block diagram of state estimation model using Chaos optimization-least square support vector machine.

In order to solve this optimization problem, Lagrange function is defined as follows.

$$L(w,b,\xi,a) = \frac{1}{2}(w^T w) + c \cdot \frac{1}{2} \cdot \sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} a_i [w \cdot \varphi(x_i) + b + \xi_i - y_i] \qquad (16)$$

where $a_i \ (i = 1, \cdots, l)$ are Lagrange multipliers.

If partial derivatives are solved and are set to zero with respect to the variables w, ξ_i, b, a according to stable point condition, the equation is as follows[9, 10, 18].

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \ \rightarrow \ w = \sum_{i=1}^{l} a_i \varphi(x_i) \\ \dfrac{\partial L}{\partial \xi_i} = 0 \rightarrow \ a_i = c \cdot \xi_i, \quad i = 1, 2, \cdots, l \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{l} a_i = 0 \\ \dfrac{\partial L}{\partial a} = 0 \rightarrow y_i = w^T \cdot \varphi(X_i) + b + \xi_i, \ i = 1, 2, \cdots, l \end{cases} \qquad (17)$$

Optimum condition is expressed as the following solution of simultaneous linear equation after removing ξ_i from the above equation.

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & \varphi(x_1)^T\varphi(x_1)+1/c & \cdots & \varphi(x_1)^T\varphi(x_l) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \varphi(x_l)^T\varphi(x_1) & \cdots & \varphi(x_l)^T\varphi(x_l)+1/c \end{bmatrix} \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} \tag{18}$$

where $\varphi(x_i)^T \varphi(x_j) = K(X_i, X_j)$, $\quad i, j = 1,\cdots,l$ (19)

and it is core function satisfying Mercer's condition.

There are several core functions including linear core function, multinomial core function, spline core function and radiation base function, and radiation base function was used in this paper as follows.

$$K(x_i, x_j) = \exp[-\frac{(X_i - X_j)^T (X_i - X_j)}{2\sigma^2}] \tag{20}$$

Deciding the critical function using the solution of equation 11,

$$f(x) = \mathrm{sgn}[\sum_{i=1}^{l} a_i \cdot K(X_i, X) + b] \tag{21}$$

where $\mathrm{sgn}(\cdot)$ is sign function.

4. Experiment and estimation result

4.1. Experiment

Charge and discharge test is done at various temperatures (-40℃, 25℃, 60℃) using battery tester "Model 13554 BATTERY HITESTER" and high and low temperature tester《WD-7015》 for Iron Phosphate Lithium Ion battery "WB-LYP 40AHA" (Fig. 2) in the experiment.

The characteristic of Iron Phosphate Lithium Ion battery "WB-LYP40AHA":

Rated capacity: 40A·h

Operating voltage: Charge-4V, Discharge-2.8V

Maximum charge current: Less than 3CA

Maximum discharge current: Constant current-Less than 3CA, Impulse current-Less than 20CA

Standard charge and discharge current: 0.5CA

Period life of charge and discharge: 80 percent depth of discharge(DOD)-More than 3000 times

70percent depth of discharge(DOD)-More than 5000 times

Operating temperature: -45℃~+85℃

Heat resisting property of case: Less than 200℃

Self-discharge rate per month: Less than 3perccent/month

Mass: 1.5Kg±50g

Charge and discharge test at various temperature.

Charge:

-Charge method: constant current-constant voltage charge

-Constant current: 0.5CA(20A), constant voltage: final charge current-down to 200mA by 4V

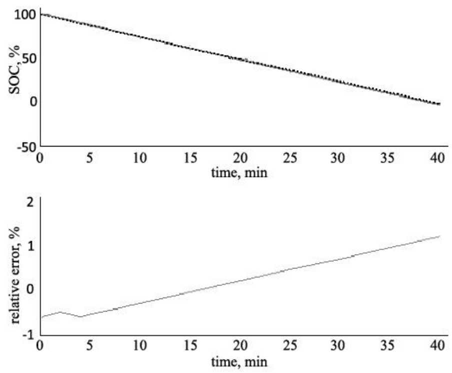
Discharge:

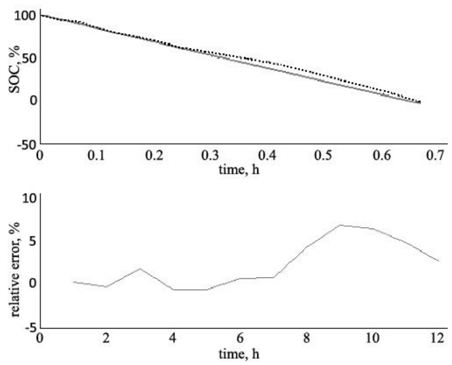
-Letting it alone for 1 hour after charge

-Discharge current 0.5CA(20A), final voltage of discharge down to2.8V

4.2. Estimation result using Chaos optimization-least square support vector machine.

Estimation result and relative error at various temperatures according to Chaos optimization-least square support vector machine estimation model from the above experimental data are shown in Figs 3, 4 and 5 in comparison with estimation result and relative error using particle filter model known as excellent estimation model in the world.

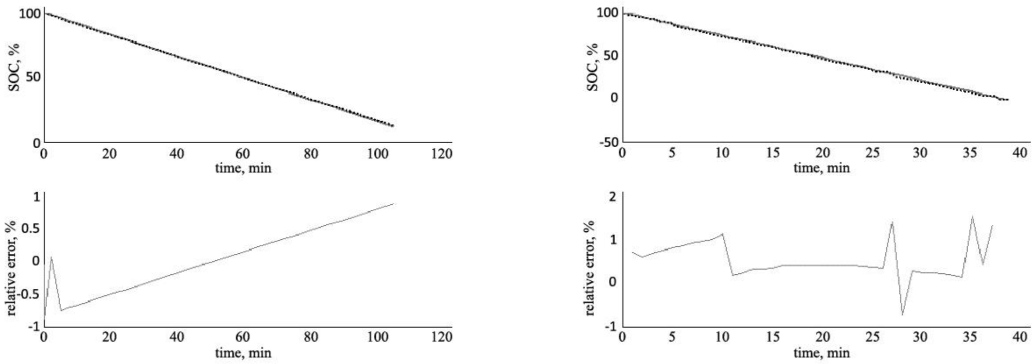




a) b)

Fig. 2. SOC estimation result and relative error using

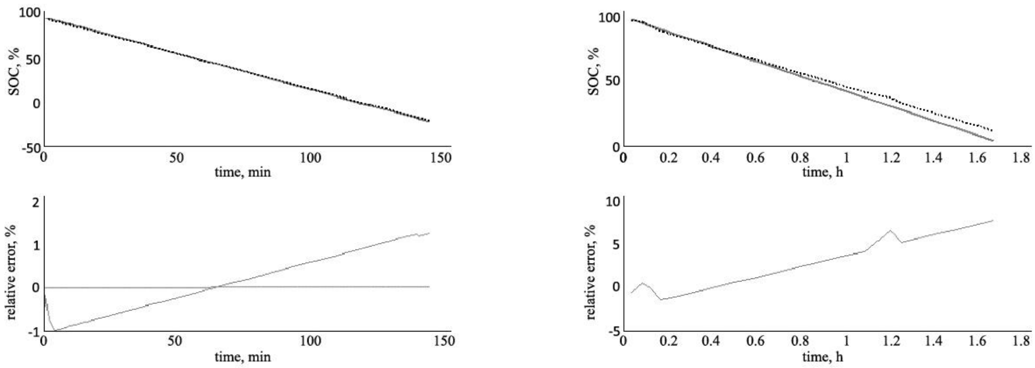
Chaos-LSSVM(a) and PF(b) at -40℃



a)
b)

Fig. 3. SOC estimation result and relative error using

Chaos-LSSVM(a) and PF(b) at 25℃.



a)
b)

Fig. 4. SOC estimation result and relative error using

Chaos-LSSVM(a) and PF(b) at 60℃.

As can be seen at Figs 3, 4, and 5 estimation result by Chaos-LSSVM is more correct than that by PF.

Calculation result of average square error for the estimation result using two estimation methods are shown at table 4.

Table 1. RMSE calculation result of SOC estimation by Chaos-LSSVM and PF at various temperatures

Estimation model	RMSE, %		
	-40℃	25℃	60℃
Chaos-LSSVM	0.1753	0.1070	0.1188
PF	0.4967	0.1770	0.3931

As we can see from table, RMSE is less than 0.5%, so there was remarkable improvement in estimating by PF, but high correctness of less than 0.2% can be ensured by Chaos-LSSVM.

5. Conclusions

In this paper, we have set the wide parameter of Gaussian kernel function and regulation parameter specified generalization ability and learning efficiency of least squares support vector machine. Next, it has selected the Gaussian kernel function and made the regression model of least squares support vector machine. Also with charge test data in various temperatures obtained through the experiment it has simulated real time SOC prediction by Chaos optimization-least squares support vector machine. As a result, we obtain conclusion to be ensured high correctness and reliability in the SOC prediction by Chaos optimization-least squares support vector machine as the correctness of less than 0.2%. However, it remains to be further clarified whether our findings could be applied to other purposes.

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